Gaussian Mixture Models Optimization for Counting The Numbers of Vehicle by Adjusting The Region of Interest under Heavy Traffic Condition

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***Abstract*—Mixture Model research has been widely implemented for numerous purpose in motion tracking applications. This method usually applied for tracking and counting the vehicles in Intelligent Transport System (ITS). In this context, Mixture Model chosen is Gaussian Mixture Model (GMM) method, due to its powerful features. Unlike many motion tracking-based methods, GMM achieves satisfactory performance from its ability to handle background subtractions. However, its implementation in detecting vehicle still have unsatisfactory result in accuration and identifying object, mainly under heavy traffic condition. The problem turn to poor accuration of object detection. Therefore, in this paper, we propose optimization of GMM performance by adjusting the Region of Interest (ROI). The propose technique to completing the report by compare the result before and after experiment in separate condition. The result show that this approach leads to improvement in tracking and counting average of accuration of motorcycle by 6.97% and car by 39.04% in several condition. Our approach to modified the method has been experimentally validated showing better segmentation performance, and this is an unbiased approach for assessing the practical usefulness of object detection methods for vehicle under heavy traffic condition on the highway.**

Keywords—gaussian mixture model; intelligent transport system; motion tracking; heavy traffic condition; region of interest.

I. Introduction

Detecting object in an image can be implemented in OpenCV (Open Computer Vision) which is integrated with the programming software. One common method for object detection is using Gaussian Mixture Models (GMM). GMM is a type of density model consisted by components of Gaussian functions, due to its powerful to perform the background adaptation process [1]. In addition, this algorithm has the reliability to light changing and object detection in repetitive conditions [2]. Menawhile, This algorithm is widely implemented in vehicle detection and calculation, including by Resmana Lim, et al. that using GMM as research method for detecting and counting vehicles, these study reach 80% accuracy using a video simulation and video samples [2]. Other research studied by Iswahyudi, et al. which combines GMM method with Kalman Filtering for tracking vehicles with low quality video, in these research found that in every condition, parameters selection must be adjusted [3]. Furthermore, previous research for vehicle counting but different method studied by Indrabayu, et al. which used Viola Jones in examining accuracy effect by the number of samples. The research found highest detection accuracy was 92%[4].

Vehicle detection optimization influenced by many factors, one of them is appropriate system parameter selection and arrangement. In this research, Region of Interest (ROI) positioning is one of parameters system used, until optimal positioning can improve the vehicle detection accuracy for heavy traffic conditions. These factors are very influential due to number of the image area, which become heavy lane of object in the main road, and having slow movement and almost stopped so when the object in sequence frames do not show movement, it will be considered as a background in GMM system because the value of the pixel will be considered as zero value [5]. For this reason, adjusting of ROI for detection and counting of vehicles in video data requires determination of the optimal ROI, so it can be focused for foreground area to be detected, and finaly the identification of the real objects that exist on the heavy traffic can be in accordance with the detection and counting results. Therefore, this result can be implemented in ITS for determining the turnover time of traffic light based on the number of vehicles in the road as in previous research that using fuzzy logic for timely adaptive traffic light [6].

II. Gaussian Mixture Model Process

Gaussian Mixture is a reliable method for the background extraction and with some modification can achieve high accuracy in background modeling [7]. This technique detecting the objects with the foreground and background subtraction from a frame of video input. In numerous computer vision applications. Background subtraction is a fundamental low-level processing task [8]. Based on the background modeling method of GMM, modeling object processed in every pixel point value. In modeling method, every pixel point's gray value in the image is regards as a statistics and stochastic process, the pixel value of pixel point can be regarded as a vector sequence, arbitrarily pixel point (x,y), its history pixel value can be expressed as:

$$\{x|, \ldots, x_r\} = \{l_i(x, y): 1 \leq i \leq r\} \quad (1)$$

There $l_i(x, y)$ refers to the gray value of pixel in time *i*. Gaussian mixture model uses K Gaussian distribution to stand for those history value, so the proportion of pixel x_t as current value is:

$$p(x, y) = \sum_{i=1}^{k} q_i, t * n(x_t, u_r, \sum r, t) \quad (2)$$

Among them, $w_{r,t}$ is the i weight of Gaussian distribution in time *t,* which reflects the appearance proportion of Gaussian distribution; $n(x_r, u_r, \sum r, t)$ is the Gaussian proportion density function when the i time's mean value $u(i, t)$ and the covariance is $\sum i, t$; $p(x_t)$ refers to the proportion of time pixel as X; K is the number of distribution. In object detection that involved extraction background there are several image processes running simultaneously. The GMM process in computer vision that implemented in this research shown in Fig. 1.

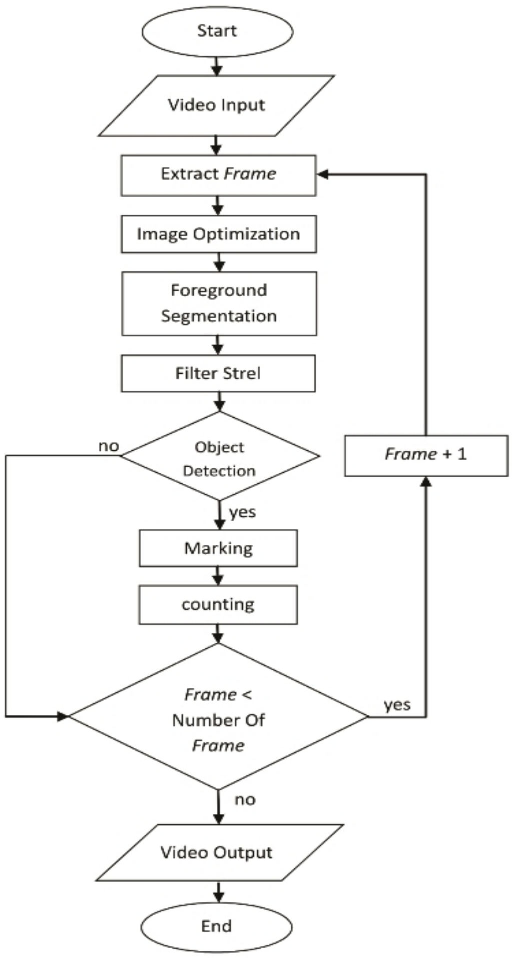

Fig. 1. GMM process

A. Video Input

The initial process in designing system for counting the number of vehicle is preparing input data. This study used some video data in various format. Input video data can be performed in different resolutions such as 160x120 pixels, 320x240 pixels, 352x288 pixels and 640x480 pixels. Sample image from video input shown in Fig. 2 (left).Video data captured by webcam. Webcam usage intended to produce low resolution video data. Webcams commonly used for remote video conference or surveillance camera. Generally webcams does not require tape or data storage, obtained data record directly transferred to a personal computer.

B. Extract Frame

Video will be extracted into frames based on video length. Afterward, these frames processed by the system.

C. Image Optimization

In image block optimization, extracted video files into several frames are processed afterward, then converting the color space from RGB to Intensity (Grayscale), so the image result in optimal condition. Thus, process on diagram block is expected to be more optimized.

D. Foreground Segmentation

Foreground segmentation conducted to distinguish between objects in foreground and background segmentation from sequence image of video input. Object criteria in the background is an unchanged object position for several frames (static position). While the criteria of object as foreground is changing objects position (moves) in each frame (dynamic position). Furthermore, the frame is converted into a binary image by thresholding. Object (a collection of pixels) detected as a background will be given binary code 0 (black), while the object (set of pixels) detected as foreground given binary code as 1 (white). Sample foreground segmentation shown in Fig. 2 (right).

E. Filter Strel

After going through the foreground segmentation process, which segmenting foreground and background, then foreground objects will be filtered to make it easier to distinguish between the object and non-object.

F. Object Detection

Vehicle detection is classification between cars and motorcycles. In this process occurs digital image segmentation that process of dividing a digital image into several parts. These parts with pixel value 1 and connected each other will be considered as one object and described in Blob. Blob in two edge coordinate point of an object, which will form a bounding box around the foreground object. This Blob existence represents the detected vehicle. Two coordinate points will be mapped to original image as a marker that the car and motorcycle has been successfully detected by the system.

G. Marking

Vehicles that have been successfully detected are marked by giving Bounding Box (BBox) around the detected vehicle object with a rectangle shape. Matlab toolbox that provides this command is *Vision.ShapeInserter*. The shape for this toolbox is set to *'Rectangle'* [9].

H. Counting

Calculation process performed by summing the vehicle from marking process. In this case vehicle that have been detected and marked with Bounding Box. The counting result will separated between cars and motorcycles, yet in one display.

I. Number Of Frame

Vehicle detection based on frames of video input will be processed to all frame from video, for example, there are 1000 frames in 1 video, then the system will process video start from first frame until the last frame.

J. Output

After all frame from video processed, then displayed as counted images and marked with Bounding Box. Looping process in handling every frame from the first frame until the last frame conducted real quick, therefore system output are shown in a video.

III. Proposed Scheme

GMM process that described earlier, there are some parameters system going on. However in this condition given treating by adjusting of ROI to evaluate its effect on vehicle detection and counting accuracy. Hence in the following figure shown the scheme of Gaussian Mixture Models optimization process by adjusting of ROI in optimal position to get the best results on heavy traffic condition. The propose technique shown in Fig. 3.

Fig. 2. Left: sample image from video, right: foreground segmentation

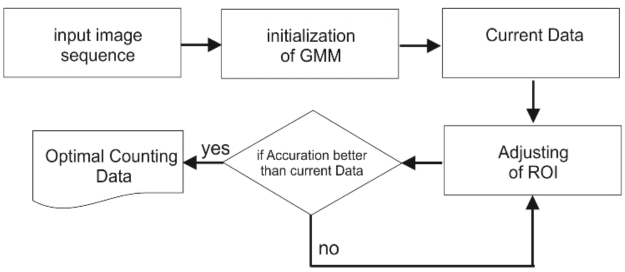

Fig. 3. Proposed scheme

A. Dataset

At this stage, video data input into the system then converted into image sequence that will be processed coninuously from one frame to the next frame until all video frames is processed. This system using the video with 160x120 pixels resolution because programming complexity are faster than the higher resolution. Video data retrieval are captured direcly to the traffic light system, thus the heavy vehicle traffic can be seen through a traffic light point. The amount of video data used is 6 file that has been taken consistently. Processed Video type is AVI with 1000 frames and 33 seconds long, which processed in Matlab software afterwards.

B. Parameter Value

ROI setting determined in 3 location; front, middle and back. To adjusting of ROI, in computer vision we used opacity function in shapes with rectangle form to covered image area that are not ROI. Part of programming processed as following pseudocode.

```
%initial roi
 1. Shape1 with rectangles border
    int32([pixel value])
 2. Shape2 with Opacity=1
 3. Setup except ROI front = step shape2
 4. Setup except ROI middle = step shape2
 5. Setup except ROI back = step shape2
 6. displayroi = step shape1
```

ROI setting parameters given by front value = ([18 84 111 36]); back = ([61 3 32 13]); middle = ([51 22 54 19]); in the frame image area. The placement of the ROI area shown in Fig. 4. Other parameters used blob for BBox. Cars and motorcycles have different blob values for minimum and maximum blob detection [10]. Before and after adjusting of ROI, blob need to analysed. But this research just using default and assumption value for minimum (min) and maximum (max) blob area. Before adjusting of ROI blob value for car: 'min'=100, 'max'=1750, motorcycle: 'min'=15, 'max'=25, and with adjusting of ROI in front detection, car: 'min'=100, 'max'= 3500, motor: 'min'=10, 'max'=50, while the middle and back detection for car: 'min'=10 'max'=100, Motor: 'min'=5 'max' =10.

C. Validation

After going through the stages of system design, then final result that will be obtained is number of vehicles and vehicle type classification and will be displayed between the number of cars and motorcycles. Although actually, the system can still make mistakes by detecting non-expected features. However, this study is focused only to evaluate the accuracy results. Thus, vehicle counting result in system design will be validated to measure the accuracy percentage. Accuration of the GMM in counting vehicles and improved accuration used the following formula:

$$\%\,Accuration\;(Acc) = \frac{True\;Positif\;(TP) of\;object}{Actual\;Object} * 100\% \qquad (3)$$

$$\%\,Improvement = \frac{Acc.object\;with\;ROI - Acc.object\;before\;ROI}{Acc\;object\;before} * 100\% \qquad (4)$$

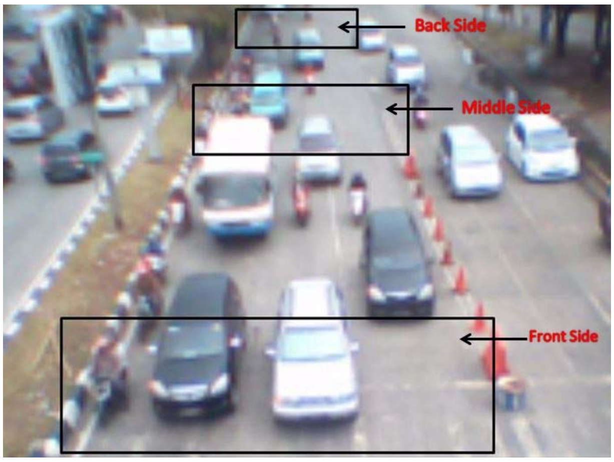

Fig. 4. Adjusting of ROI

IV. Results and Discussion

Based on dataset using 6 sample video data, with 160x120 pixels of resolution, testing results for detecting and counting before and after technique implemented obtained as follows:

A. Motorcycle Counting Result

Based on Table I shows that before adjusting of ROI, the motorcycle counting result leads to 69.21% average accuracy, and Table II shows better result for Motorcycle counting by Adjusting of ROI. In the front of ROI leads to average by 74.03%, in the middle by 55.74% and in the back by 27.09%. Then these result calculated by (4) to evaluate before and after adjusting of ROI, with compare based on optimum result of Table II (front), and the result leads to improvement the average of accuration by 6.96% .

B. Car Counting Result

Based on Table III shows that before adjusting of ROI, the car counting result leads to 62.18% average accuracy, and Table IV shows better result for car counting by Adjusting of ROI. In the front of ROI leads to average by 79.72%, in the middle by 83.27% and in the back by 86.46%. Then these result calculated by (4) to evaluate before and after adjusting of ROI, with compare based on optimum result of Table IV (back), and the result leads to improvement the average of accuration by 39.05%.

TABLE I. MOTORCYCLE COUNTING RESULT BEFORE ADJUSTING OF ROI

Data	Actual	True Positif of Motorcycle	
		a	acc (%)
1	132	89	67.42
2	129	88	68.22
3	130	98	75.38
4	186	140	75.27
5	128	78	60.94
6	150	102	68.00
Average			69.21

a = counting result, acc = accuration

TABLE II. MOTORCYCLE COUNTING RESULT WITH ADJUSTING OF ROI

Data	Actual	True Positif of Motorcycle					
		a	acc (%)	b	acc (%)	c	acc (%)
1	132	93	70.45	52	39.39	25	18.94
2	129	109	84.49	97	73.48	51	38.64
3	130	92	70.76	88	69.84	42	33.33
4	186	104	55.91	72	40.22	25	13.97
5	128	98	76.56	70	55.55	50	39.68
6	150	129	86.00	84	56.00	27	18
Average			74.03		55.74		27.09

a = front, b = middle, c = back, acc = accuration

TABLE III. CAR COUNTING RESULT BEFORE ADJUSTING OF ROI

Data	Actual	True Positif of Car	
		a	acc (%)
1	57	35	61.40
2	32	25	78.13
3	39	26	66.67
4	50	33	66.00
5	46	20	43.48
6	54	31	57.41
Average			62.18

a = counting result, acc = accuration

TABLE IV. CAR COUNTING RESULT WITH ADJUSTING OF ROI

Data	Actual	True Positif of Car					
		a	acc (%)	b	acc (%)	c	acc (%)
1	57	45	78.94	41	70.68	43	74.14
2	32	28	87.50	28	87.50	29	90.63
3	39	35	89.74	38	92.68	38	92.68
4	50	48	96.00	44	88.00	45	90
5	46	18	39.13	36	80.00	39	86.67
6	54	47	87.03	42	80.76	44	84.62
Average			79.72		83.27		86.46

a = front. b = middle. c = back. acc = accuration

C. Discussion

Basically, Adjusting of ROI will affect the foreground and background substraction areas of system interest in detecting and counting vehicles. From wide image area in motion, this limitation area makes background subtraction analysis process running optimally, due to the lack of image noise. However from the experimental results shown that, motorcycle and car detection gave opposite accuracy variation of ROI traversed by the object.

Optimal motorcycle detection and counting leads to better result by adjusting front of ROI, with larger scope area. while for the car, optimal detection and counting leads to better result by adjusting back of ROI, with smaller scope area. The results could have occurred, because the vehicle foreground segmentation covered in region of interest. From the Increase calculation accuracy of the motorcycle, the average increase is 6.97% and the car at 39.04%. The graphical illustration of vehicle detection and calculation result (cars and motorcycles) by adjusting of ROI shown in Fig. 5 and 6.

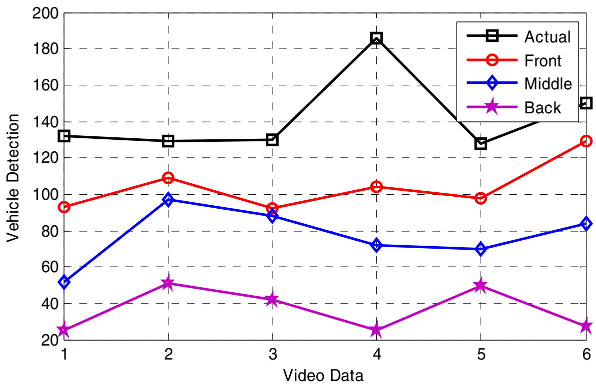

Fig. 5. Graphic Counting of Motorcycle Detection

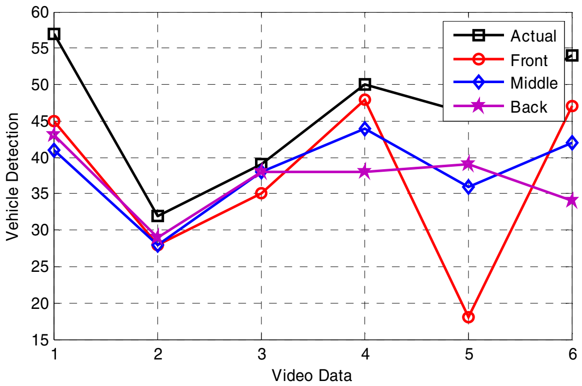

Fig. 6. Graphic Counting of Car Detection

V. CONCLUSION

From the experimental data results shown that the implementation of Gaussian Mixture Models for 120x160 video resolution, with adjusting of ROI for detection and counting of vehicles on the main road with a heavy traffic condition leads to better approach. The influenced effect varies for the type of vehicle, for motorcycle improvement the average of accuration by 6.97%, and car with average raised by 39.04%.

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